Association between the Energy and Emission Prices: An analysis of EU Emission Trading System

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Abstract

Previous studies have focused on the co-movements between the prices of different types of energy and, to some extent, the co-movements between the energy and financial assets prices, falling short of analysing the co-movements between the different types of energy and emission price. In this study, using the daily data from November 2007 to 31st October 2017 on quotes of Brent Crude oil and Natural Gas spot returns and quotes of the EU-ETS spots, we employed a time-varying copulas connection function to assess the risk dependency relationship between ETS and energy prices. The results show that there is an asymmetry dependence change rule between ETS, oil and gas spot index, with the correlation of the lower tail significantly higher than that of the upper tail. These findings indicate that, with the use of time-varying SJC Copulas model, economic agents can control investment risk and forecast abnormal fluctuations in oil prices.

Keywords: ETS, Emissions Trading, EU-ETS spots, Energy Prices, Time-varying Copula model
JEL: C22, O13, P18, P48, Q4

1. Introduction

A large body of literature shows how forecasts for crude oil and natural gas prices can be improved by modelling the dependence structure and co-movements in their prices (see, amongst others, Kang et al., 2009; Mohammadi and Su, 2010; Chang et al., 2010). Existing studies on this subject have tended to focus on the joint dynamics between WTI, Brent crude oil and natural gas spot log returns, which are captured by many statistical techniques, such as a copula, Monte Carlo simulations and bootstrap-based goodness-of-fit tests (for instance, see, Jschke, 2014; Alexander, 2015)

The stochastic dependence modelling in energy, equity, commodity and exchange rate markets has become ever more common in applications. The argument is that crude oil plays a major role in many types of investments, including equity, commodity and foreign exchange markets (see, for example, Aloui et al., 2013; Wu et al., 2012; Reboredo, 2012). In modelling price dependence in energy markets, Gregoire et al. (2008) examined the dependence structure of log-returns of futures on crude oil and natural gas and found that the dependence between the prices of crude oil and natural gas is roughly constant with time. However, a study by Accioly and Aiube (2008), investigating the dependence of crude oil and gasoline prices, found that there is a change in the behaviour of prices in more recent periods compared to those at the beginning of the decade. This change is observed through different copula models and the results were confirmed by using a bootstrap analysis. A later study by Reboredo (2011) modelled the dependence structure between crude oil benchmark prices utilising copulas using weekly data to assess whether markets were regionalised or globalised on the basis of upper and lower tail dependence. The study concluded that markets with well-developed forward and future markets exhibit greater conditional dependence and that globalisation hypothesis holds as oil prices move together, independently of whether the market is booming or crashing. The study found that with globalised crude oil markets, price co-movements could possibly have implications for risk diversification strategies and asset pricing models.

It is prima facie evident in the existing literature that the problem of modelling and assessing risk measures in energy portfolios, using various techniques, is extensively covered. However, the significance of energy tax, measured by the EU's emissions trading system (EU-ETS) on energy prices and its effect on the energy price co-movements, to the best of our knowledge, has not been addressed hitherto. Yet, it is worth emphasising that the co-movements of ETS and energy prices are also crucial for government planning since they affect the overall economy of both oil consuming and producing countries. Concomitantly, this paper covers a topic of broad applicability and high practical relevance in the area of risk management and risk diversification strategies. The current literature has not sought to link oil and gas price behaviour to EU-ETS price movements, this paper contributes to the current understanding of the joint dynamics between crude oil and natural gas by throwing an important determinate, namely EU-ETS price, into this mix to investigate the existing price co-movements. By focusing on the relationship between emission price and energy prices, we provide new insights into an area that has been under studied in the energy and resource economics literature.

To assess the risk dependency relationship between ETS and energy prices, we employed a time varying copulas connection function. Our key findings suggest that there is an asymmetry dependence change rule between ETS and Oil and gas spot index, with the correlation of the lower tail significantly higher than that of the upper tail. The findings indicate that the use of time-varying SJC Copulas model can control investment risk and forecast abnormal fluctuation in oil prices.

The remainder of this paper is organised as follows: Section 2 briefly discusses the EU-ETS framework. Section 3 introduces the development of the time-varying Copula model and its parameter estimates. In Section 4, the analysis of the data features is presented, along with the empirical test of the model. Section 5 concludes this paper.

2. The Dependence of EU ETS and Energy Prices

The EU Emission Trading System (EU-ETS) is a cap-and-trade approach that was developed by the European Union (EU) to reduce greenhouse (GHG) concentration under the Kyoto Protocol in lieu of a much wider, but rejected, CO_2 emissions tax or carbon tax. The greenhouse gases cover Carbon Dioxide (CO_2), Nitrous Oxide (N_2 O) and Perfluorocarbons (PFCs). Several GHG emissions trading systems, based on the Kyoto Protocol signed in 1997, have been established in the USA, Australia and New Zealand but the EU ETS, launched in 2005, is considered the largest and most liquid emissions trading international market.

The EU-ETS provides limits to a considerable part of the EU's emissions and is in line with Kyoto's Protocol of emissions trading provisions. As the CO_2 covered installations (e.g. polluters through power generation or gas flaring) were allowed to trade allowances freely within the EU, the EU ETS cap-and-trade approach was intended to ensure not only that overall emissions would be reduced, but also that the cuts are made by those firms that can achieve the most efficient cost reduction (European Commission, 2003). Considering that the annual market tradable allowances are granted to the scheme participants at the beginning of each phase, these allowances, which are priced daily by the market, reflect new liquid assets which can be regarded as the opportunity cost of carbon at the market price (Sijm et al. 2006).

Production in excess of allowances does require a direct purchase from the market of an allowance, concomitantly, the payment of allowance (i.e. price of carbon) could be a change in technology that results in more CO_2 emissions or that some of the scheme participants chose the more expensive option of replacing hard coal by gas, which is translated into higher demand and prices of allowances. One might argue that the price of EU ETS, therefore, reflects the switching costs between the different types of fuels by the energy-intensive industries, which are the significant contributors to CO_2 emissions in the EU. Thus, the supply function is convex, discontinuous, uncertain and variable throughout the year, reflecting the switching costs between primary fuels (Bunn et al., 2007). Reducing a tonne of CO_2 within a year by the scheme's participants is expected to evolve through onto the prices of different types of fuels. Carbon allowances are traded daily, and their prices are factored in both the supply and demand of all types of fuels, including crude oil and gas. Moreover, the supply of tradable allowances evolves through the year on the annual equilibrium price of carbon (Bunn et al., 2007). Primary fuel switching (e.g. from coal to gas and vice versa) in a closed system with no other switching costs between primary fuels (i.e. technology, transportation cost, operational cost) could be a significant determining factor in oil and gas market pricing. While fuel-switching is an important factor in the pricing of energy, changes in global economic outlook, supply and demand fundamentals and geopolitical risk cannot be underestimated in oil and gas pricing. Global economic forecasts drive demand for oil and downbeat forecasts could lead to a fall in oil and gas prices and vice versa. Concerns over the adequacy of oil supplies which mainly attributed to insufficient production capacities is another potential price driving factor for oil and gas markets. However, one can argue that the global economic outlook is factored in ETS price since ETS contract auctions are meant to reflect economic growth forecasts and the emission associated with. With the ability of OPEC to raise large volume of oil supply at short notice, any distribution in oil supplies is usually a short-lived problem, so the impact on oil and gas prices is minimal. The co-movement between geopolitical risks and oil price is still not fully appreciated and the current literature is still not conclusive on any correlation between energy price and geopolitical risks. One could potentially have a better understanding of the co-movement between emission price and energy price if geopolitical risk is accounted for but, due to measurement difficulties, this paper is limited to investigating the co-movement between ETS and energy prices.

The argument here is that carbon price is important in formulating the equilibrium price of crude oil and gas, and that it is, in effect, an exogenous variable in the oil pricing model. Putting a price on carbon gives a financial value to emissions saved, which gives incentive to covered installations to invest in clean and low-carbon technology to cut emissions, leading to a fall in demand for high-carbon fuels. Despite the fact that the ETS is a European scheme aimed at reducing carbon emissions within the EU, allowing covered installations to buy credit permits from emission-saving installations around the world, the emission trading scheme provides incentives for investment in low–carbon technology, which also contributes to the fall in demand for high-carbon fuels. However, the mechanism of supply and demand cannot always provide an explanation of the ETS market price. Figure 1 shows the EU ETS price fluctuations from 2009 to 2017 and that the price is about 48 percent lower than it was in the middle of the credit crunch. The economic and financial crisis, along with the progress in achieving GHG emissions targets by the scheme participating countries, have resulted in a negative impact on the carbon price. Also, exogenous interactions between ETS and energy efficiency instruments reduce the demand form allowances and places downward pressure on the carbon price.

Figure 1: EU- ETS Historical Prices from 2009 -2017

3. Time-Varying Copula Model

The multi-dimensional variables correlation index is usually illustrated by linear correlation. However, this correlation has some inherent limitations because fluctuations differ according to conditions, whereby the correlation between variables unavoidably changes. This is particularly the case for financial markets subject to sudden and extensive changes. Such irregular variations in the market cannot be depicted by linear correlation. Subsequently, the time-varying correlation model should be used when explaining the tail. The tail correlation description allows the verification of whether another substantial market fluctuation could be induced by an earlier incidence of similar fluctuations. Copula function is mostly applicable for verifying the correlation of the tail. If copula $C(u,v)$ does exist, the lower tail correlation and the upper tail correlation of the variables can be expressed as follows:

$$\tau^{L} = \lim_{u \to 0} \frac{C(u,u)}{u} \quad , \tau^{U} = \lim_{u \to 1} \frac{1-2u+C(u,u)}{1-u} \tag{1}$$

However, there are many copulas, each with different characteristics. The Standard Copula and the t-Copula, for example, are not fit to depict the asymmetry of the financial markets; Gumbel Copula cannot grasp the lower tail correlation; Clayton Copula falls short of grasping the upper tail correlation; Frank Copula, on the other hand, cannot establish both the upper and the lower tail correlation. When compared with the common Copula, the JC Copula is notably superior in describing both the lower and the upper tail correlation. Nevertheless, it is affected by the asymmetry in describing the joint distribution of the same correlation in both the lower and the upper tail. An alternative way to capture time variation in the series and to overcome this deficiency of the other types of copulas is to use regime switching function as suggested by Patton (2006). This function has been widely used in the correlation calculations pertaining to the financial market and financial capital. In this paper, we follow Patton (2006) and assume the following dynamics for SJC – Copula:

$$C_{SJC}(u,v|\tau^U,\tau^L)=0.5[C_{JC}(u,v|\tau^U,\tau^L)+C_{JC}(1-u,1-v|\tau^U,\tau^L)+u+v-1] \quad (2)$$

In practice, when studying the tail correlation using copula function, the relevant parameters of the tail τ^U and τ^L are assumed to be constant for simplicity. However, assuming that fluctuations are constant, the correlation of the sequences in fluctuation are obtained in relation to time. The mean absolute difference between τ^U and τ^L over the previous 10 periods is used to measure how far the standard error is from the condition of a total positive dependence. The expectation of this distance measure is inversely related to the concordance ordering of copulas; under perfect positive dependence it will equal zero, under independence it equals 1/3, and under perfect negative dependence it equals ½ (Patton, 2006).

In order to highlight the feature of constant variation, a process similar to an ARMA (1,10) type process can be used to describe the correlation of the upper and the lower tail of SJC-Copula (Patton, 2006; Bhatti, 2006). We assume the following dynamics for the SJC copula:

$$\begin{cases} \tau_t^L = \wedge(\omega_L+\beta_L\tau_{t-1}^L+\alpha_L\frac{1}{10}\sum_{j=1}^{10}|u_{t-j}-\nu_{t-j}|) \\ \tau_t^U = \wedge(\omega_U+\beta_L\tau_{t-1}^U+\alpha_U\frac{1}{10}\sum_{j=1}^{10}|u_{t-j}-\nu_{t-j}|) \end{cases} \quad (3)$$

Where $\wedge(x)=(1-e^x)/(1+e^x)$ guarantees that τ^U and τ^L remain in the (-1,1) range and τ^U and τ^L are the two parameters measuring the dynamic structure of the tail, and thus characterise the time-variation function. The parameters and the tail correlation parameters of the time-varying function SJC-Copula have one-to-one correspondence, thus allowing the asymmetry, the tail features as well as the correlation of the market, subject to significant fluctuations, to be defined.

4.1 Data and Descriptive Statistic

We examined the co-movements between two energy spot prices and the EU-ETS prices. The study used the daily quotes of Brent crude oil and Natural Gas spot return, covering the period from Nov 2, 2007 to Nov 2, 2016, obtained from Bloomberg. Compared with weekly data, daily data tends to smooth the tails of the returns distribution. Historically, Brent traded with a small premium to WTI spots, with a significant widespread at times. The overall strong correlation between the two crude oil grades, however, in risk management and risk optimisation, means that there is still a need to consider and stimulate all portfolio holdings for portfolio risk diversification reasons.

We also used daily quotes of EU ETS spot from Jan 3, 2008 to Oct 31, 2017. The reason for choosing 2008 as the start date for the analysis is because the period from 2005 – 2007 was the first trading period, however, the number of allowances, based on estimated needs, turned out to be excessive. The over-supply of tradable allowances led to a gradual fall in the price of permits to zero in 2007. The EU-ETS covers approximately 11,000 power stations and manufacturing plants in the 28 EU Member States, plus Iceland, Liechtenstein and Norway, as well as aviation activities in these countries. In total, around 45% of total EU greenhouse gas emissions are regulated by the EU ETS (European Commission, 2016).

4.2 Modelling Marginal Time Series

As a first step in estimating the dependence structure between the variables, using copula, which is a multivariate distribution function, C_0, with a standard uniform marginal distribution, we performed the standard Ljung-Box test statistics on the observed and square observed log-returns to detect whether the time series is exhibiting autocorrelation. We added squared lagged log-returns from other variables into the mean and variance equations to test the assumption that the information used to identify the underlying copula is also the same for marginal copula. The Ljung-Box statistics reported in Table 1 show that the null hypothesis of no autocorrelation through 15-lags is clearly rejected at a 5 per cent level of significance. We also performed the Augmented Dickey-Fuller (ADF) unit root tests on the log of spot prices. As shown in table 1, the null hypothesis that a unit root is present (i.e. non-stationarity) in the time series cannot be rejected for natural gas, crude oil and EU ETS at 5 per cent level of significance. When applying the ADF tests in the first difference, the null hypothesis of a unit root is clearly rejected for log natural gas, crude oil and EU ETS at 5 per cent level of significance.

Table 1: ADF and Jarque-Bera Tests

	NG	BC	ETS
Sample size	2470	2470	2470
Mean	0.569	1.860	0.815
Median	0.556	1.911	0.876
Jarque-Bera Test	3.212*	2.476*	1.542*
$p-value$	(0.000)	(0.000)	(0.000)
ADF Unit-Root Test	63.182*	73.281*	89.101*
$p-value$	(0.000)	(0.000)	(0.000)
Auto Corr – *r*	-0.003*	-0.001*	-0.061*
Lag 1	-0.016	-0.071	-0.012
Lag5	-0.041	-0.015	-0.021
Lag10	0.002	0.071	0.011
Lag 15	0.001	0.014	0.081
Ljung-Box (15)	31.42*	66.20*	56.71*
$p-value$	(0.000)	(0.002)	(0.000)

* Indicates significant at the 5% level of significance ** NG, BC, ETS are Natural Gas, Brent Crude Oil and EU ETS respectively.
** Lag length are selected to examine a range of possible autocorrelations.

The next step was to employ the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) using the Lagrange Multiplier (LM) tests proposed by Engle (1982) on the residuals from a simple OLS regression of each returns series on the lagged values in order to test the null hypothesis of no ARCH effects. The results in Table 2 show that the null hypothesis of no ARCH effects and the null hypothesis of no GARCH effects are both rejected for all series under study. These results are not sensitive to the number of lags included in the Lagrange Multiplier tests and GARCH tests. Given these results of table 2, the GARCH effects need to be cleared before the extreme value analysis is used

Table 2: GARCH Test

Testing for ARCH (1)	NG	BC	ETS
F-statistic	42.4*	31.6*	19.1*
$p-value$	(0.000)	(0.000)	(0.000)
Testing for GARCH (1.1)	NG	BC	ETS
nR^2	42.3*	31.8*	18.8*
$p-value$	(0.000)	(0.000)	(0.000)

* Indicates significant at the 5% level of significance ** NG, BC, ETS are Natural Gas, Brent Crude Oil and EU ETS respectively.

To estimate the marginal models, we adopted an AR (*1*) – GARCH (*1,1*) model, assuming that the return on asset is:

$$r_t = \mu + \sigma_t \varepsilon_t \qquad (4)$$

Where r_t is the return on asset at time t and ε_t is a sequence of $N(0,1)$ random variables. We also define the residual return a time t, $r_t - \mu$ as

$$\chi_t = \gamma_t \sigma_t \qquad (5)$$

$$\sigma_t^2 = \alpha + \beta_0 \sigma_{t-1}^2 + \beta_1 \varepsilon_{t-1}^2 \qquad (6)$$

Where $\alpha > 0$ and $\beta_1 \geq 0$ to ensure both positive variance and $\beta_1 < 1$ in a stationary process (e.g. weak and strong). Table 3 presents the results for both the parameters and the standard errors for the marginal distribution models. It is apparent that, in the variance equation, all parameter estimates are significant, with notably very strong autoregressive effect in the situation of volatility. The necessary and sufficient condition for covariance stationary of ε_t is that all the Eigen-values are less than one, which is the case for all three series. The results also denote the long-lasting effects of a shock to any of the three times series variables.

Table 3: Marginal Distribution Model

	NG	BC	ETS
Constant	0.024*	0.081	0.021
	(0.012)	(0.015)	(0.001)
AR (1)	-0.032*	-0.021	-0.012*
	(0.014)	(0.064)	(0.001)
GARCH (1)	0.921	0.943	0.910
	(0.001)	(0.013)	(0.008)
ARCH (1)	0.016*	0.082*	0.022*
	(0.001)	(0.007)	(0.002)
Residual ARCH			
F-statistics	0.941	1.891	0.875
$p - value$	(0.9120	(0.271)	(0.881)

* Indicates significant at the 5% level of significance ** NG, BC, ETS are Natural Gas, Brent Crude Oil and EU ETS respectively.
** Standard errors are in parentheses.

4.3 Copula Estimations

Observations from scatter plots of bivariate standardised residuals in figure 2 endorse the association of the standardised return residuals. It shows a strong tendency of the two pairs, namely crude oil/ETS and NG/ETS, to move together regardless of their marginal distribution. While one would expect to see this kind of strong association with crude oil and WTI, as their log returns originate from similar types of crude oil (Jäschke, 2014), and to some extent with natural gas, the association with crude oil, natural gas and ETS is surprising. ETS would normally have a different log returns from both types of crude oil and natural gas.

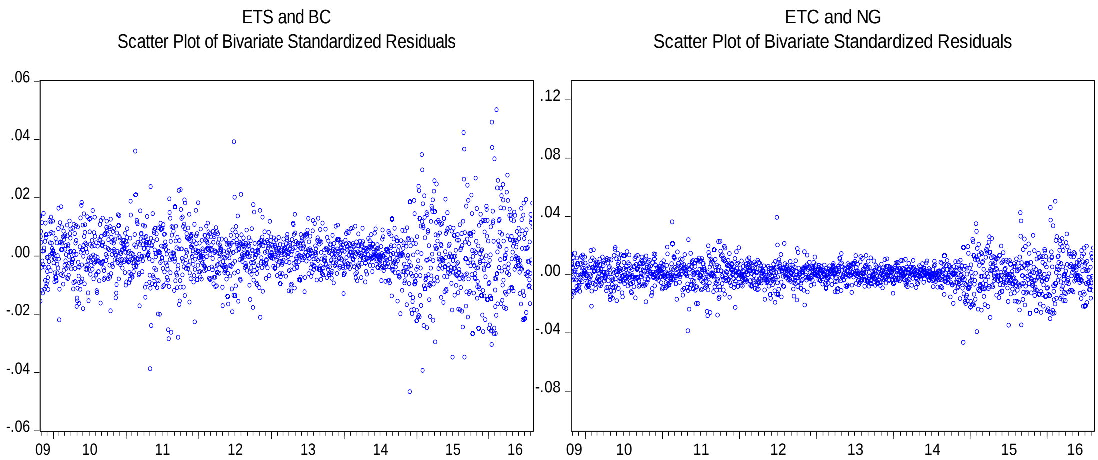

Figure 2: ETS, Brent Crude (BC) and Natural Gas (NG) Copulas

Copulas are then, estimates of the nature of the dependence between energy and emissions price. Table 4 reports the results of parameter estimates for time varying dependence copulas. The results show that all the estimated parameters are significant. In line with previous studies, the results also show a high dependence structure between energy prices. Similar also to previous studies, the results show a higher lower tail dependence between energy price, which means that both crude oil and natural gas are closely dependent at times of high volatility in the energy market.

Table 4: Time Varying Copula

	NG/BC	BC/ETS	NG/ETS
Upper $\hat{\omega}$	0.57	0.87	2.67
	(0.000)	(0.000)	(0.262)
Upper $\hat{\beta}$	0.077	-3.68	-7.196
	(0.000)	(0.328)	(0.051)
Upper $\hat{\alpha}$	-0.70	2.21	-6.48
	(0.000)	(0.291)	(0.001)
Lower $\hat{\omega}$	3.32	1.92	8.64
	(1.290)	(2.061)	(0.174)
Lower $\hat{\beta}$	-7.21	-6.92	9.11
	(0.012)	(1.812)	(3.120)
Lower $\hat{\alpha}$	1.291	3.301	0.927
	(0.000)	(0.022)	1.201)
Copula Likelihood	1,231.6	1,632.0	347.5

* Indicates significant at the 5% level of significance ** NG, BC, ETS are Natural Gas, Brent Crude Oil and EU ETS respectively.
** Standard errors are in parentheses.

Overall, the lower tail dependence is higher than the upper tail dependence (see figure 3), meaning that energy prices in pairs and also energy and emissions price are more likely to move down together than go up together. That is very significant in the gas/ETS dependence structure; however, the dependence structure by no means is stable over time. The results also show that the dependence between energy and emission price is not symmetric.

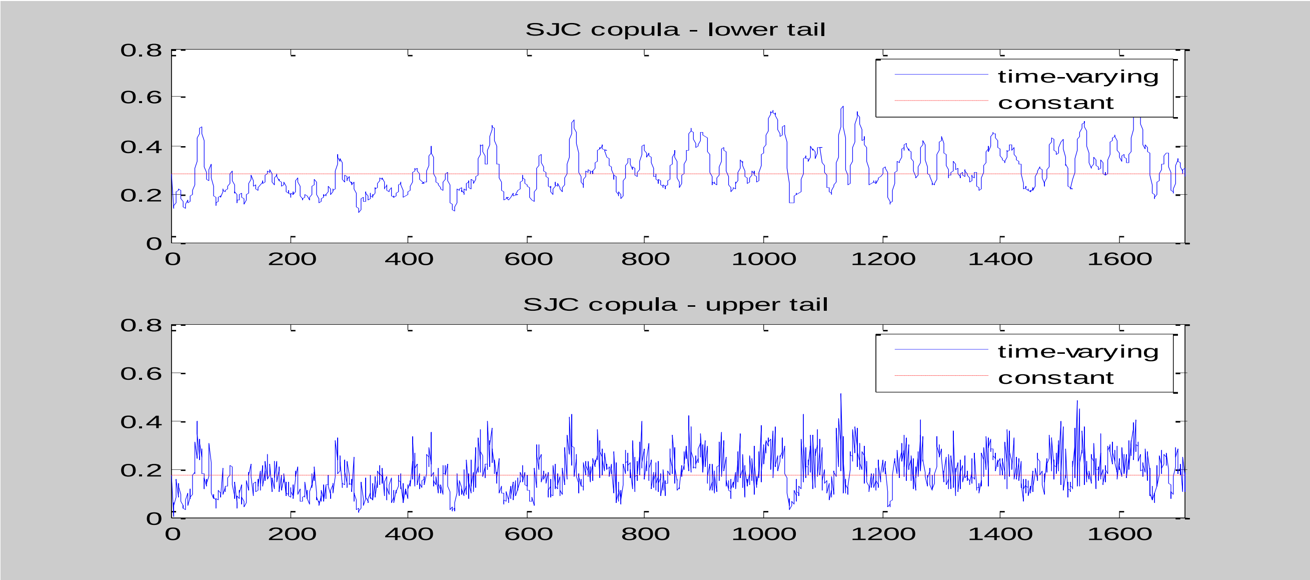

Figure 3: SJC Copula Lower and Upper Tail

5. Conclusions

This paper analysed the co-movements between energy price and EU-ETS, applying the time varying SJC copula model. As shown in the results there exists a proportionate correlation between ETS and both types of energy, namely crude oil spot price and natural gas spot price. In measuring the tail correlation of constant correlation of SJC-Copula, the correlation of the lower tail dependence is higher than the upper tail dependence, meaning that energy prices in pairs and also energy and emissions price are more likely to move down together than go up together. Previous studies mainly focused on the co-movement between all types of energy but fell short of investigating the possible correlation between energy price and ETS. The recent decline in the price of ETS has never been linked to the movements in the price of energy. The ETS market has struggled for years under an enormous surplus of spare allowances depressing prices. The fall in ETS price could be attributed to fuel switching from coal to the more environmental friendly natural gas, leading to the oversupply of ETS allowances and depressing the ETS allowances price. Moreover, the decline in the ETS allowances due to the fall in coal power generation and rising renewables deployment could also put a downward pressure on energy price. One could argue that the current price level in the EU ET is far below the €20-30/t needed to trigger key abatement measures, like fuel switching from coal to gas in most countries. Despite the price of carbon allowances falling, energy intensive industries are actually emitting less carbon dioxide into the atmosphere than before, due to the increase of renewables deployment, which could possibly explain the decline in energy price as well. The results of the tail dependency also shed some light on the co-movements between energy price and ETS allowance price. The low price of ETS allowances is associated with the low price of energy for a significant period of time. It is noteworthy that, in terms of the investment portfolio, risk management and assets pricing, the depiction of the correlation of energy price and ETS, and the tail dependency structure, is of great significance. The deeper understanding of the co-movements between different types of energy and oil price which is useful in assessing the likelihood of alternative hedging strategies, and to design appropriate mechanisms to speed up revenue diversification. This paper's findings will have potentially significant impacts on risk diversification and hedging strategies for both commodity traders and institutional investors in addition to policymakers.

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